



Ain Shams University
Faculty of Engineering
Computer and Systems Engineering Department

Automatic Human Face Analysis and Description

A Thesis

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Submitted by:

Yomna Safaa El-Din Salah El-Din

B.Sc. of Electrical Engineering
(Computer and Systems Engineering Department)
Faculty of Engineering - Ain Shams University, 2008

Supervised by:

Prof. Hani Kamal Mahdi
Professor in the Computer and Systems Eng. Dept.
Faculty of Engineering - Ain Shams University

Dr. Mohamed Nabil Moustafa
Associate Professor in the Computer and Systems Eng.
Dept.
Faculty of Engineering - Ain Shams University

June 2013
Cairo

Statement

This dissertation is submitted to Ain Shams University for the degree of Master of Science in Electrical Engineering (Computer and Systems Engineering).

The work included in this thesis was carried out by the author at the Computer and Systems Engineering Department, Faculty of Engineering, Ain Shams University, Cairo, Egypt.

No part of this thesis was submitted for a degree or a qualification at any other university or institution.

Name: Yomna Safaa El-Din Salah El-Din

Date: June, 2013

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Yomna Safaa El-Din Salah El-Din
Computer and Systems Engineering Department
Faculty of Engineering
Ain Shams University
Cairo, Egypt
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Dedication

To Yassin, my son and gift from God.

Abstract

This thesis presents an approach for gender recognition from 2-D facial images, based on the fusion of several local-texture information at the decision-level. Our aim is to achieve high classification rates of human gender by building robust image representations using features extracted from specific face regions. Moreover, we target a boosted performance through integrating several single-feature classifiers.

We focus on gender classification for its potential applications in the fields of surveillance, security and marketing. Knowing the gender information should help face identification systems in avoiding unnecessary comparisons which should affect positively both speed and accuracy. We extensively evaluate the proposed framework on the gender classification problem, although other face related tasks such as face detection, facial expression recognition or face authentication could also be considered.

We first investigate a number of state-of-the-art image representations based on local features descriptors: Local Binary Patterns (LBP), Histogram of Gradients (HOG), and Haar-like features. We have also investigated adding a simple shape based feature that depends on facial landmarks positions.

We then propose a novel face-image representation that combines both texture and shape information. Our representation is based on extracting Scale Invariant Feature Transform (SIFT) descriptors at some predefined points on the face representing locations of several facial landmarks. The proposed face representation showed to be competitive with descriptors that extract local-texture information from the whole face image.

Additionally, we propose two methods for combining the decisions of multiple individual classifiers into a single robust gender decision. Our first merging technique is based on the Naive Bayes classifier, while the other method relies on the image information itself added to the classifiers individual decisions.

The experimental results are evaluated on four different face-image datasets. The first two are famous benchmark datasets: FERET and Labeled Faces in the Wild (LFW) which are publicly available and provide a variety of images' conditions. The third dataset is the UB KinFace database, which is a public set of images collected from the Internet, and finally, a privately collected set of images that include different ethnicities.

Experiments demonstrated robustness of our approaches in both controlled and uncontrolled conditions. Correct gender classification

accuracy of above 97%, 95%, 94% and 95% were achieved on FERET, LFW, KinFace and the private dataset respectively.

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List of Symbols

LBP	Local Binary Patterns
HOG	Histograms of Oriented Gradients
SIFT	Scale Invariant Feature Transform
FERET	Facial Recognition Technology database
LFW	Labeled Faces in the Wild
HCI	Human-Computer Interaction
FLD	Fisher Linear Discriminant
NN	Neural Networks
SVM	Support Vector Machine
PC	Principal Component
PCA	Principal Component Analysis
ICA	Independent Component Analysis
LDA	Linear Discriminant Analysis
GA	Genetic Algorithm
MLBP	Multi-resolution Local Binary Patterns
LGBMP	Local Gabor Binary Mapping Pattern
LDP	Local Directional Pattern
IDP	Interlaced Derivative Pattern
YGA	Yamaha Gender and Age
ASM	Active Shape Model
AAM	Active Appearance Model
LUT-Adaboost	Look-Up Table Adaboost
PGA	Principal Geodesic Analysis
CNN	Convolutional Neural Network
ROI	Region of Interest
QP	Quadratic Programming
LS-SVM	Least-Square Support Vector Machine
RBF	Radial Basis Function
MoE	Mixture of Experts

CMC

Cumulative Match Curve

List of Publications

- [1] Y. S. El-Din, M. N. Moustafa, H. Mahdi, “A Mixture of Two Gender Classification Experts”, *the 25th SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI), Brazil*, IEEE Computer Society, pp. 245-251, August 2012.
- [2] Y. S. El-Din, M. N. Moustafa, H. Mahdi, “Gender Classification Using Mixture of Experts from Low Resolution Facial Images”, *the 11th International Workshop on Multiple Classifier Systems (MCS2013), Nanjing University, China*, pp. 49-60, May 2013.
- [3] Y. S. El-Din, M. N. Moustafa, H. Mahdi, “Landmarks-SIFT Face Representation for Gender Classification, *the 17th International Conference on Image Analysis and Processing (ICIAP 2013), Italy*, September 2013.

Chapter 1

Introduction

Facial analysis has been widely investigated in computer vision, including gender, age and expression classification. In particular, gender discrimination has been a long standing challenge in the area of soft biometrics to add intelligence in security and commercial applications. It is a challenging pattern recognition problem that involves a process of determining whether the person whose face is in the given image or video is a man or a woman.

Face images analysis has been successfully used in many applications ranging from biometric to robotic-human interaction. Particularly, gender recognition has a high application potential in some places where people should be served depending on their gender, such as supermarkets, restaurants and security surveillance in building entrances. Gender classification is useful for marketing and advertising through the collection of costumer statistics and demographic information for what is called ‘gender-based advertising’.

The correct recognition of gender can improve the performance of face recognition and face verification systems [3] by using separate models for each gender [4–6]. This is done when gender classification is used as a prior step to face recognition which narrows down the search space to only half the subject database. Moreover, successful gender classification helps the process of indexing and retrieval of images [7], and is also useful for training computer aided systems that interact with human beings: Human-Computer Interaction (HCI) whose software behavior is adjusted with respect to the user’s gender.

This chapter introduces the problem of gender recognition, discusses the challenges involved, and briefly presents our approach highlighting the contributions of the thesis. After we have stated